Causal Relationship and Volatility Spillover between Chinese CSI 300 Index and Index Futures

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Abstract

The CSI 300 is a market index that reflects the performance of the Chinese stock market by tracking the price fluctuations of 300 major stocks traded in China. This paper examines the causal relationship and volatility spillover between two prices of the CSI 300, the one in the stock market and the one in the futures market. Empirical studies on various developed markets show that changes in futures prices can help predict changes in stock prices. In other words, the futures market play a dominant role in the price discovery process. A study by Yang, Yang, and Zhou (2010), however, find that the above relationship does not apply to the CSI 300. High barriers of entry to the futures market are cited as a possible explanation. The data we use in this paper, prices of the CSI 300 from March 2015 to September 2015, cover a period of low entry barriers in the first three months and a period of rising barriers afterwards. By using a vector error correction model (VECM) for mean causality, we find that changes in futures prices cause changes in stock prices in the sense of Granger (1969) when barriers are low, and is non-causal when barriers are high. We also use an extended Q-test for volatility spillover and find evidence of bi-directional volatility spillover when barriers are low but only unidirectional futures-to-stock spillover when barriers are high.

1. Introduction

In an efficient market, prices of a stock index and its futures contract should move simultaneously. Prices in one market should not contain more information than prices in the other market. This relationship, however, is not supported by empirical studies. It is well-documented that prices in the futures market can help predict prices in the stock market in various countries.[1] According to Tse (1999), the futures market are more likely to reflect new information ahead of the stock market because of its "inherent leverage, low transaction costs, and lack of short sell restrictions."

China launched its first stock index futures contract, the CSI 300 index[2] futures, in 2010. Yang, Yang, and Zhou (2011) examine the price discovery performance[3] of the new futures contract by using the first four months' of trading. They find that, contrary to what is observed in developed markets, the stock market, instead of the futures market, plays a dominant role in the price discovery process. High barriers to entry at the time are cited as possible explanations, including qualification exams, balance requirements, and margin requirements[4] (Yang, Yang, and Zhou, 2011).

Our research question is then concerned with how the index futures market performs now five years after its launch. Balance requirements have remained unchanged in the past five years despite inflations. Margin requirement has been reduced[5]. It is also certain that in the ensuing five years that more people have passed the qualification exams. With the barriers lowered, it is likely that China's index futures

[1] See Kuotmos &Tucker (1996), and Tse (1999) for evidence in the U.S. market, Booth et al. (1999) for German, and So & Tse (2004) for Hong Kong.

[2] The CSI 300 is a capitalization weighted index that tracks the performance of 300 A-share stocks listed on the Shanghai or Shenzhen Stock Exchanges. The stocks included are among the top 300 A-share stocks in terms of capitalization and are highly liquid.

[3] According to Yang, Yang, Zhou (2011), "price discovery in futures markets is commonly defined as the use of futures prices to determine expectations of (future) cash market prices."

[4] Balance requirement refers to the requirement that investors should have a minimum balance in their trading account before investing in the futures market. Margin requirement refers to the requirement that an investor need to maintain a certain percentage of the total value of commodity traded as deposit.

[5] According to Yang, Yang, and Zhou (2011), margin requirement in 2010 for the CSI 300 was 15% or 18% depending on the contracts. Prior to August 26, margin requirement in 2015 was 10%.

market has become more aligned with those in developed markets by 2015. Our data from March 2015 to early June cover this period of low entry barriers.

Our data also cover a period of rising barriers following the market crash in June 2015. Within two month after the peak on June 12, the CSI 300 lost more than 40% of its value. In response, the Chinese government adopted a bracket of policies aimed at halting the selloff. In particular, the China Financial Futures Exchange (CFFEX), where the CSI 300 futures index is traded, had put forward drastic measures. The margin requirements for the CSI 300 futures contract increased from 10% to 12%, 15%, and 20% respectively in three days after August 26, and eventually reached 40% on September 7th. Furthermore, stringent limits on single account intraday trading volumes were enforced: from September 7th, any single account could only buy or sell 10 contracts within one day, whereas the limit was 1200 in July. Moreover, the transaction fee increased from 0.23‱[6] pre-crisis to 23‱ by September. As previously mentioned, the futures market reflects new information faster partly because of its high leverage and low transaction fees. The above policies seriously curtailed the scope of those advantages and are likely to adversely impact the price discovery performance of index futures.

In this paper we will examine the causal relationship between stock index prices and index futures prices using high frequency data from the CSI 300 index and its futures for the three months before the stock market crash in June 2015 and three months after the crash. Specifically, we test for causality in the sense of Granger (1969) between the prices in the two markets using a two variable vector error correction model (VECM). Our test of Granger non-causality from the futures market to the stock market will indicate the futures market's price discovery performance, which is defined as "the use of futures prices to determine expectations of (future) cash market prices" (Yang, Yang, and Zhou, 2011). It is worth pointing out that in this paper the only variables that we use are the stock price and the futures price. This

[6] Transaction fee is calculated as a percentage of the total value of the commodity traded, regardless of leverage. For example, the transaction fee of a commodity worth 10000 Yuan is 23 Yuan after the fee raise, even though the actual transaction amount is only a fraction of 10000 Yuan because of leverage.

simplistic two-variable causality model has its pitfalls: we have not accounted for possible causality linkages between the two prices through other variables. Moreover, in this two variable model non-causality one step ahead will imply non-causality up to any arbitrary future horizon (Dufour and Renault, 1998). Including other potentially relevant variables such as investor sentiment[7] and establish causality chains might be an interesting topic, but it is beyond the scope of this paper.

Furthermore, we test possible volatility spillover between the two markets by modeling the conditional volatility of the error terms obtained from the previous VECM. Our test is based on the Q-test proposed in Ljung and Box (1978) and an extension of the spillover test proposed in Hong (2001). Our paper contributes to the current literature by examining the price discovery performance of Chinese stock index futures after five years of its initial launch. We investigate whether the index futures' price discovery performance has become more aligned with those observed in developed markets. Furthermore, the changing levels of barriers to entry after the stock market crash serves as a natural experiment. We use data from that period to provide empirical evidence for the theory that high barriers of entry hurt the price discovery performance of the futures market.

We find that changes in CSI futures prices consistently Granger cause changes in CSI stock prices during the pre-crash period. Significant volatility spillover exists in both directions, i.e. from the futures market to the stock market and vice versa during the pre-crash period. After the stock market crash, the futures prices have less consistent effects on stock prices. Futures prices can help predict stock prices in some sub-periods but not in others. In the first few days following the introduction of each new barriers, futures prices invariably have no prediction power. There is still significant volatility spillover from the futures market to the stock market after the crash, but there is no evidence for the other direction. The above results have two main implications. First, it provides evidence that barriers to entry indeed affects the price discovery performance of the futures market, confirming what is suggested by finance theory.

[7] A causality chain might be established as such: price movements at time t in the futures market cause changes in public sentiment at time t+1 which in turn cause changes in the stock market at t+2. In this case, there is non-causality from the futures market to the stock market one step ahead but causality two steps ahead.

Second, the results might indicate that changes in prices and changes in volatility are transmitted through different channels between the stock market and the futures market. The rest of the paper is organized as the follows. Section 2 presents the theoretical model. Section 3 introduces the empirical data, followed by the empirical model in Section 4. Section 5 discusses the size and power of the test statistics in our empirical model through Monte Carlo simulation. Section 6 presents the empirical results, and Section 7 concludes.

2. Theoretical Model

According to Stoll and Whaley (1990), the theoretical relationship between stock prices and futures prices in a perfectly efficient and continuous futures market without transaction costs is guided by the following equation:

$$P_{F,t} = P_{S,t}\, e^{(r-d)(T-t)} \tag{1}$$

where $P_{F,t}$ and $P_{S,t}$ are the prices for futures and stock markets at time *t*, *r* is the interest rate, *d* the dividend on the stock , and *T* the expiration time of the futures contract. The owner of a stock's futures contract at time t is obligated to buy the stock at time T from the current owner of the stock, so an equilibrium price to pay is the cost incurred by the stock owner who "carries" the stock through period t to T. The total cost of carrying a stock of price $P_{S,t}$ is then $e^{(r-d)(T-t)}$ times of its price assuming continuously compounding interest rates.

If we take the natural log of the above equation, we get:

$$\ln(P_{F,t}) = \ln(P_{S,t}) + (r-d)(T-t) \tag{2}$$

If we then define return as the log price differentials, we get:

$$\begin{aligned} R_{F,t} &= \ln(P_{F,t}) - \ln(P_{F,t-1}) \qquad (3) \\ &= [\ln(P_{S,t}) + (r-d)(T-t)] - [\ln(P_{S,t-1}) + (r-d)(T-(t-1))] \\ &= R_{S,t} - (r-d) \end{aligned}$$

Thus, in a perfectly efficient market, prices and returns in the two markets should move simultaneously. It is worth mentioning that the assumption of continuous compounding is not necessary. If the interest rate is compounded for each discrete time interval, the cost of carrying a stock is simply $P_{S,t}\ (1 + r - d)^{(T-t)}$, and the conclusion of simultaneous movement will still hold.

However, in practice, different trading costs such as transaction fees and tax in the stock market and the futures market create frictions to the above relationship. According to Fleming, Ostdiek, and Whaley (1996), traders with new information will first execute trades in the lowest-cost market to generate the highest profit. As a result, the futures market, which tends to have lower transaction costs than the stock market will play a dominant role in the price discovery process. In other words, when new information changes the equilibrium price, futures price will move to the new equilibrium price faster than stock prices. Thus, changes in futures prices can help predict changes in stock prices, and we say that the futures price leads the stock price. The high leverage in the futures market further reinforces this lead: traders will be able to produce higher profit with less capital when leveraged.

We model the behaviors of traders by incorporating the above mentioned trading frictions. We assume that: 1) the traders have an investable budget of C dollars; 2) the futures market has a leverage ratio[8] of r: 1, where r is larger than 1; 3) the transaction costs in the stock market is S_1 and in the futures market it is S_2 , where S_1 and S_2 are fixed for each transaction and their differential $S_1 - S_2$ is positive; and 4) the cost-of-carry relationship holds before new information comes in, and $r = d$ so that $P_{F,t} = P_{S,t}$; 5) when new information comes in at time t , the equilibrium price of the stock and its futures contract becomes P^*, and traders have perfect information about this change before the market price actually moves to P^*.

[8] The leverage ratio is the ratio of the value of a commodity to the deposit paid to buy/sell that commodity. For example, with a deposit of $100 an investor can "own" a commodity of $1000 when the leverage ratio is 10:1. This significantly increases the profit/loss potentials of an investor: if the commodity price rises by 10%, i.e. $100, the return on investment is $100/$100, or 100%. But if the commodity price drops by 10%, the investor will lose all his investment. Note that leverage ratio is the reciprocal of margin requirement.

Thus, the profit of investing in the stock market at time t is:

$$Profit_{S,t} = \frac{|P^* - P_{S,t}|}{P} C - S_1 \tag{4}$$

and the profit of investing in the futures market at time t is:

$$Profit_{F,t} = \frac{|P^* - P_{F,t}|}{P} rC - S_2 \tag{5}$$

It is obvious that $Profit_{F,t}$ is strictly larger than $Profit_{S,t}$ when $P_{F,t} = P_{S,t}$, so traders will only trade in the futures market until $P_{F,t+n}$ becomes close enough to P^* at a certain $t + n$ such that $\frac{|P^* - P_{S,t+n}|}{P} C - S_1 \geq \frac{|P^* - P_{F,t+n}|}{P} rC - S_2$. Note that this happens only when $\left|P^* - P_{S,t+n}\right| \geq |P^* - P_{F,t+n}|$, so at time $t + n$ the price of the futures contract is closer its equilibrium price than the stock price is, and the futures price leads the stock price.

All the above discussed trading frictions are observed in China. Prior to the stock market crash in 2015, the margin requirement for index futures is 8%, so they are highly leveraged. Transaction costs are 0.23‰ for index futures and transactions are tax exempt. On the other hand, tax per transaction alone accounts for a 10‰transaction cost in the stock market. Trade rules in China favors futures markets even more: while investors in the stock market are required to hold their newly-opened positions at least until the next trading day (called T+1 policy), futures markets have no such restrictions so investors can cash out anytime during the trading hours. In sum, our theoretical model suggests that the futures market should play a dominant role in the price discovery process in China before the stock market crash. In other words, past futures prices can help predict future stock prices. This provides justification for our use of lagged causality empirical models in section 4.

3. Data

We obtain intraday 5-min level closing prices for the CSI 300 and its futures contracts from March 8, 2015 to September 17, 2015 from Bloomberg[9]. The data cover 67 trading days before the stock market crash and 67 trading days afterwards. The Chinese stock market crash started on June 12, so we separate our data by defining March 8 to June 11 as the pre-crash period and June 12 to September 17 as the post-crash period. All statistical tests will be performed separately on the two periods. There are several reasons for doing this. First, our models assume a linear trend in stock prices, but our data contain a break in trend: pre-crash prices show a strong upward trend and post-crash data show a strong downward trend. Hence, it will be improper to fit the two periods to a single model of linear trend. More importantly, we also have reasons to believe that the markets operate in different ways before and after the crash. The period before the crash is one generally without policy changes and government interventions, while the post-crash period not only saw panic in public sentiment but multiple changes to trading rules.

We also clean up the data by accounting for the differences between the stock market and the futures market. First of all, for each stock there are four futures contracts trading simultaneously with different expiration dates and they usually have different prices. In order to construct a single futures price series, we follow the precedent in the literature by using prices from nearby month contracts[10] until the expiration week. For the expiration week we use prices from the next nearby contract. For example, the expiration week for the March contract is the week ending on March 20, so futures prices before that week are collected from the March contract and afterwards from the April contract. We use nearby month contracts because it is the most actively traded and switch before expiration to avoid expiration-day effects.[11]

Second, futures markets and stock markets in China trade during slightly different time periods within a day. The stock exchanges start trading from 9:30 a.m. to 11:30 a.m. in the morning and then from 1:00

[9] Bloomberg L.P. Retrieved through Bloomberg Terminal at Park Library, University of North Carolina at Chapel Hill

[10] The nearby month contract refers to the contract that has the closet expiration date.

[11] Similar techniques for constructing futures price series see Fleming, Ostdiek, and Whaley (1996), Koutmos and Tucker (1996), Tse (1999).

p.m. to 3:00 p.m. in the afternoon. However, the futures market for the CSI 300 index futures opens from 9:15 a.m. to 11:30 a.m., and then from 1:00 p.m. to 3:15 p.m. . We follow Yang, Yang, and Zhou (2011) by excluding prices prior to the first prices available for the stock index in the morning and after the last record in the afternoon. We also notice there are sometimes futures prices reported for 12:55 p.m. and we eliminate them as well. By excluding the data above, we avoid a trivial case of causality, or spurious causality, from one price to the other: when only the stock or the futures contract trades, it is obvious that the price of the asset being traded can help predict (future) prices of the other non-trading asset once it starts trading.

Finally, we use the natural log of prices following Koutmos and Tucker (1996) for simplicity of calculation. In the end, we get 49 prices for each trading day, and that translates into a sample size of 3283 for both the pre-crash and post-crash data sets.

4. Empirical Model

4.1 Causality in Mean

It is a recognized fact that financial time series have unit roots. In other words, financial time series are not stationary on levels, but are difference-stationary. Fama (1970) provides both theoretical support and empirical evidence in his seminal paper on the topic of Efficient Market Hypothesis (EMH). Unit root process can lead to the problem of spurious regression, where correlations between covariates are confounded by a mutual time trend (Granger and Newbold, 1974; Engle and Granger, 1987). The price of a stock and the price of its futures contract indeed share a mutual time trend as indicated by the cost-of-carry relationship discussed in the previous section. Thus we take the log difference of both stock prices and futures prices, constructing two so-called log return series. We then empirically test the existence of unit root in both the price series and the log return series through an Augmented Dickey–Fuller (ADF) test and a Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The null hypothesis for the former test is that there is a unit root and the null hypothesis for the latter is there is not a unit root. We find that the

ADF test is not rejected for both stock index and stock index futures price series and is rejected for both return series at 0.05 significance level, and the opposite is true for the KPSS test. This strongly indicates that both price series have one unit root. Thus it is proper for us to investigate the causal relationship between stock index and stock index futures prices through a vector error correction model (VECM) (Engle and Granger, 1987; Tse, 1999).

The VECM model has the form:

$$\Delta P_t = \alpha(\beta' P_{t-1} + u) + \sum_{i=1}^{q} B_i \, \Delta P_{t-i} + \mu + \varepsilon_t \tag{6}$$

We can write it more explicitly as:

$$\begin{bmatrix} \Delta P_{S,t} \\ \Delta P_{F,t} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \left([\beta_1 \; \beta_2] \begin{bmatrix} P_{S,t-1} \\ P_{F,t-1} \end{bmatrix} + u \right) + \sum_{i=1}^{q} \begin{bmatrix} b_{i,11} & b_{i,12} \\ b_{i,21} & b_{i,22} \end{bmatrix} \begin{bmatrix} \Delta P_{S,t-i} \\ \Delta P_{F,t-i} \end{bmatrix} + \begin{bmatrix} \mu_S \\ \mu_F \end{bmatrix} + \begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{bmatrix} \tag{7}$$

where $\Delta P_{S,t}$ and $\Delta P_{F,t}$ are log returns of the stock prices and futures prices. We can also observe that the first term in the above equation can be written as $\alpha_1(\beta_1 P_{S,t-1} + \beta_2 P_{F,t-1})$ and $\alpha_2(\beta_1 P_{S,t-1} + \beta_2 P_{F,t-1})$. $(\beta_1 P_{S,t-1} + \beta_2 P_{F,t-1})$ is the "error correction" term which is assumed to be a stationary process with mean 0. α_1 and α_2 are called "adjustment terms", and they measure the impact of short run deviations on stock returns and futures returns respectively. The above model might include a dummy variable for trend in ΔP_t; however, we do not observe any obvious trend in the return series and we follow the precedents in Koutmos and Tucker (1996) and Tse (1999) to only include constant terms μ_S and μ_F, which indicate linear trends in levels, i.e. prices. We also include a constant u in the error correction term.

We then test the statistical significance of the estimated parameters using a Wald test. The null hypothesis for Granger non-causality from futures prices to stock prices is $b_{i,12} = 0$ for all lags i. The null hypothesis for Granger non-causality from stock prices to futures prices is $b_{i,21} = 0$ for all lags i. We choose the number of total lags to include in our model based on minimizing the Akaike information criterion (AIC).

Furthermore, according to Yang, Yang, and Zhou (2011), we can test the hypothesis $\alpha_1 = 0$: the null hypothesis indicates that disequilibrium has no impact on stock returns. In other words, stock prices lead future prices in the sense that stock prices are exogenous, and any adjustments back to long run equilibrium take place in the futures market. We will also test the hypothesis $\alpha_2 = 0$, where the null indicates future prices lead stock prices.

4.2 Volatility Spillover

Volatility spillover exists between the stock market and the futures market if a change in volatility in one market Granger causes a change in volatility in another. According to Hong (2001), "volatility is often related to the rate of information flow", so studying volatility spillover may help us better understand the information transmission mechanism between the two markets.

4.2.1 Volatility Spillover Q-test

It is a stylized fact that financial time series are heavy tailed and often display conditional heteroscedasticity. A key question is whether the volatility dynamics of the market index returns and futures returns are intertwined after a discrete time lag. We therefore test the spillover effects between index return volatilities and futures return volatilities by doing a Q-test in the spirit of Box and Pierce (1970) and Ljung and Box (1978), based on an extension of the method in Hong (2001). The null hypothesis of volatility spillover from one asset to another is equal to zero cross correlation at all displacements of standardized conditional volatility errors for those assets (Hong, 1996). The detailed test procedures are as follows:

(1) We fit univariate GARCH (1, 1) models by quasi-maximum likelihood (QML) to the residuals $\hat{\varepsilon}_{S,t}$ and $\hat{\varepsilon}_{F,t}$ from the previous VECM. The GARCH models are:

$$\hat{\varepsilon}_{i,t} = \sigma_{i,t} z_{i,t}, z_{i,t} \sim i.i.d.(0,1) \tag{8}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \hat{\varepsilon}_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \tag{9}$$

for $i \in \{S, F\}$. $\sigma_{i,t}^2$ denotes the conditional variance for return series *i* at time *t*.

(2) We compute the sample cross-correlation function between the centered squared standardized residuals $\left\{\hat{u}_{i,t} = (\frac{\hat{\varepsilon}_{i,t}}{\hat{\sigma}_{i,t}})^2 - 1\right\}$ and $\left\{\hat{u}_{j,t} = (\frac{\hat{\varepsilon}_{j,t}}{\hat{\sigma}_{j,t}})^2 - 1\right\}$. The correlation function at lag h for return series *i* and *j* is

$$\hat{\rho}_{ij}(h) = \left\{\hat{C}_{ii}(0)\hat{C}_{jj}(0)\right\}^{-\frac{1}{2}}\hat{C}_{ij}(h) \tag{10}$$

$$\hat{C}_{ij}(h) = \begin{cases} T^{-1}\sum_{t=j+1}^{T} \hat{u}_{i,t}\hat{u}_{j,t-h}, & h \geq 0 \\ T^{-1}\sum_{t=-j+1}^{T} \hat{u}_{i,t+h}\hat{u}_{j,t}, & h < 0 \end{cases} \tag{11}$$

hence $\hat{C}_{ii}(0) = T^{-1}\sum_{t=1}^{T}\hat{u}_{i,t}^2$ and $\hat{C}_{jj}(0) = T^{-1}\sum_{t=1}^{T}\hat{u}_{j,t}^2$. T is the sample size.

(3) The Ljung-Box Q-statistics is defined as:

$$Q_{ij}(h) = T(T+2)\sum_{k=1}^{h}\frac{\hat{\rho}_{ij}^2(k)}{T-k} \tag{12}$$

Under the null hypothesis of no spillover, $Q_{ij}(h) \rightarrow \chi^2(h)$ in distribution. We therefore compare $Q_{ij}(h)$ to α-level critical values $\chi_{1-\alpha,h}^2$ from the chi-squared distribution, and reject at level α if $Q_{ij}(h) > \chi_{1-\alpha,h}^2$.

We should note that $Q_{ij}(h)$ is a uni-directional test statistics for volatility spillover from return series *i* to return series *j*. To test bi-directional volatility spillover between the stock market and the futures market, we define

$$Q_{SF}(h) = T(T+2)\sum_{k=1}^{h}\frac{\hat{\rho}_{SF}^2(k)}{T-k}, \ h > 0 \tag{13}$$

$$Q_{FS}(h) = T(T+2)\sum_{k=1}^{h}\frac{\hat{\rho}_{FS}^2(k)}{T-k}, \ h > 0 \tag{14}$$

Then if $Q_{SF}(h)$ is larger than its corresponding critical value $\chi_{1-\alpha,h}^2$, we conclude there is volatility spillover from the stock market to the futures market up to lag h at α significance level , and vice versa if $Q_{FS}(h)$ is larger than $\chi_{1-\alpha,h}^2$.

4.3 Rolling Window Analysis

Since our data covers a long period of time during market turmoil, we perform a rolling window analysis of our model to account for the possible non-stationarity within the data. We first pick a fixed window size $\mathrm{m} = 500$, estimate the model using the first *m* observations, and then perform Wald tests based on VECM model estimates. We then update the window to cover observations from 2 to $\mathrm{m} + 1$, re-estimate the model, and perform the tests. We repeat this iteration for all remaining windows. We then plot the P-values for all sub-periods. For the volatility spillover test, however, we set our window size to $\mathrm{m} = 2500$ because the test has low power with smaller sample sizes. This will be shown in our simulation studies below.

5. Simulation

5.1 Simulation Design

Since the power of both the Wald test in the Granger causality section as well as the Ljung-Box Q test in the volatility spillover test is based on asymptotic theories, we have reason to believe that they might not work well in finite samples. We perform simulation studies to investigate the empirical size and power of the Wald and Ljung-Box tests discussed above. Specifically, we simulate two VECM time series, one with non-zero diagonal terms in the B matrix of equation (6) and the other with zero diagonal terms respectively to model causality and non-causality. We then estimate VECM parameters using the simulated time series and perform Wald test on the null hypothesis that the diagonal terms are zero. We repeat this process for 10,000 times. With large sample sizes, empirical size should match the nominal size, i.e. the significance level, and the empirical power is expected to be close to 1.

Similarly, we investigate the finite sample properties of our volatility spillover test by simulating two GARCH processes. In the first case the time series will be generated by two independent univariate GARCH processes, so there is no volatility spillover by construct. The two time series in the second case are generated a bivariate GARCH model where volatility spillover is included. We then apply our volatility spillover test on simulated data.

Last but not least, to mitigate the influence of initial values on our simulated time series, we adopt a burn-in period of size n: we simulate a time series of sample size $2n$, and only use the second half of the data for our tests. We do this for both the VECM simulation and the volatility spillover simulation.

5.2 Simulation Result

5.2.1 VECM Wald Test Simulation Results

The data generating process is a VECM of lag 1 with zero mean:

$$P_{i,t} = P_{i,t-1} + \Delta P_{i,t} \tag{15}$$

$$\begin{bmatrix} \Delta P_{1,t} \\ \Delta P_{2,t} \end{bmatrix} = \begin{bmatrix} -0.01 \\ 0.004 \end{bmatrix} \left([1, -1] \begin{bmatrix} P_{1,t-1} \\ P_{2,t-1} \end{bmatrix} \right) + \begin{bmatrix} 0.7 & b_{i,12} \\ 0.3 & 0.7 \end{bmatrix} \begin{bmatrix} \Delta P_{1,t-i} \\ \Delta P_{2,t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{16}$$

Where $\varepsilon_{S,t}$ and $\varepsilon_{F,t}$ are i.i.d. Normal (0, 1) random variables. For our non-causality case, we set $b_{i,12} = 0$, so there is no causality from futures return to stock return. We set $b_{i,12} = 0.2$ for causality case. We test the hypothesis of $b_{i,12} = 0$ on the above two cases by simulating 10,000 samples with three different sample sizes: 500, 2500, and 5000. We choose large sample sizes to be comparable with the empirical sample size of our Chinese stock market data. We report the rejection rate for the 10,000 samples under three significance levels: 1%, 5%, and 10%. We set initial values $P_{1,0} = P_{2,0} = 0$. The results are shown in the table below.

Table 1: VECM Causality Test Rejection Frequencies

Sample Size	500			2500			5000		
Significance Level	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1
Rejection Rate H0	0.0132	0.0586	0.1110	0.0118	0.0548	0.1064	0.0114	0.0524	0.1022
Rejection Rate Ha	1	1	1	1	1	1	1	1	1

The results in Table 1 show that our Wald test for Granger-causality in VECM has good size and power under different significance levels and for various sample sizes. The rejection rate is 100% for all cases under the alternative hypothesis, and the rate is close to nominal significance level under the null. We see that empirical size approaches the significance level as sample size increases, but it is already reasonably close even with a sample size of only 500.

5.2.2 Bivariate GARCH Volatility Spillover Test Simulation Results

The data generating process is a bivariate GARCH (1, 1) ~~as in Aguilar & Hill (2015):~~

$$y_{i,t} = h_{i,t} z_{i,t}\,,\;\; z_{i,t} \sim Normal(0,1) \tag{17}$$

$$\begin{bmatrix} h_{1,t}^2 \\ h_{2,t}^2 \end{bmatrix} = \begin{bmatrix} 0.3 \\ 0.3 \end{bmatrix} + \begin{bmatrix} 0.3 & a_{12} \\ 0 & 0.3 \end{bmatrix} \begin{bmatrix} y_{1,t-1}^2 \\ y_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} 0.6 & b_{12} \\ 0 & 0.6 \end{bmatrix} \begin{bmatrix} h_{1,t-1}^2 \\ h_{2,t-1}^2 \end{bmatrix} \tag{18}$$

We simulate three levels of volatility spillover: no spillover, weak spillover, and strong spillover where a_{12} takes 0, 0.1, and 0.3 respectively and b_{12} takes 0, 0.3, and 0.6 respectively. We simulate 10,000 samples with sample size 1000, 2500, and 5000 for each volatility spillover level and each significance level 1%, 5%, and 10%. Lags tested are 1, 2, 3, 4, 5, 10, 15, and 20. We set our initial values $y_{1,0}^2 = y_{2,0}^2 = h_{1,0}^2 = h_{2,0}^2 = 0$. The results are reported in the tables below.

Table 2: Volatility Spillover Test Rejection Frequencies: No Spillover

Sample Size	1000			2500			5000		
Lags	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1
1	0.0105	0.052	0.1046	0.0104	0.0457	0.0958	0.0107	0.0512	0.1041
2	0.0097	0.0485	0.1002	0.01	0.0508	0.099	0.0085	0.0478	0.0987
3	0.0114	0.0517	0.1026	0.0108	0.0526	0.101	0.0095	0.048	0.0918
4	0.0111	0.0514	0.1017	0.0124	0.0528	0.1049	0.0109	0.0497	0.0964
5	0.0102	0.0535	0.1021	0.0124	0.0535	0.1041	0.0123	0.0499	0.098
10	0.0107	0.0497	0.1046	0.012	0.0516	0.1045	0.0109	0.0499	0.0971
15	0.0128	0.0557	0.1081	0.0121	0.0531	0.105	0.0106	0.0478	0.0989
20	0.0111	0.0555	0.1023	0.0116	0.0541	0.1046	0.0115	0.0488	0.0957

Table 3: Volatility Spillover Test Rejection Frequencies: Weak Spillover

Sample Size	1000			2500			5000		
Lags	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1
1	0.0854	0.1854	0.267	0.1683	0.3321	0.4398	0.3507	0.5657	0.6719
2	0.2257	0.396	0.5022	0.5491	0.7369	0.8161	0.8788	0.9551	0.9744
3	0.3921	0.5868	0.6857	0.8175	0.9231	0.9522	0.9891	0.9975	0.9989

4	0.5141	0.706	0.7888	0.9376	0.9789	0.9885	0.9991	1	1
5	0.6034	0.785	0.8545	0.9724	0.9922	0.9966	1	1	1
10	0.7158	0.8639	0.9164	0.9952	0.999	0.9997	1	1	1
15	0.6756	0.8365	0.8977	0.9935	0.9989	0.9997	1	1	1
20	0.6234	0.7997	0.8733	0.9885	0.9985	0.9992	1	1	1

Table 4: Volatility Spillover Test Rejection Frequencies: Strong Spillover

Sample Size	1000			2500			5000		
Lags	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1
1	0.1713	0.3222	0.4139	0.4001	0.6072	0.7049	0.717	0.8691	0.9159
2	0.3931	0.5886	0.6897	0.815	0.9202	0.9554	0.9888	0.9978	0.9999
3	0.5934	0.7648	0.8422	0.9627	0.9887	0.9937	0.9999	1	1
4	0.7136	0.8577	0.9078	0.9904	0.998	0.9992	1	1	1
5	0.7858	0.9005	0.9388	0.9976	0.9996	0.9998	1	1	1
10	0.8629	0.946	0.971	0.9998	0.9999	1	1	1	1
15	0.831	0.9303	0.9612	0.9997	0.9998	1	1	1	1
20	0.7866	0.9038	0.9437	0.9992	0.9998	0.9998	1	1	1

From the no spillover case in Table 2, we see that the test has good size for all three sample sizes and all significance levels. From the weak spillover case in Table 3, we see that the test has low power, especially for lower lags, when the sample size is 1000. When we increase the sample size to 2500 and 5000, the test has reasonably high power starting from the 3rd lag. In the strong spillover case, power is generally higher than the weak spillover case but is still low when sample size is 1000. It has high power after the 2nd lag for sample size 2500 and 5000. This indicates that our spillover test works is expected to perform well at any lag, including small lags. The sample sizes for both the pre-crash period and the post-crash period are 3283. However, we will not be able to perform this spillover test in our rolling window analysis as the window size will be too small for the test to have reasonable power.

6. Empirical Results

6.1 VECM Results

We estimate our VECM model with a standard Engle-Granger 2-step OLS method (Engel and Granger, 1987). Furthermore, it is a stylized fact that financial time series often display heteroscedasticity, and we suspect that the error terms in our VECM will then have unknown forms of heteroscedasticity as a result, so we estimated a heteroscedastic-robust covariance matrix according to White (1980). We then perform Wald test using the obtained covariance matrix.

[Table 5]

From Table 5, we observe that AIC reaches its minimum at the 10^{th} VAR lag. The actual lag in VECM is then 1 less than its VAR lag. So we choose total lag j to be 9.

[Table 6]

[Table 7]

Table 6 and Table 7 report the results from the Wald tests for the pre-crash period and post-crash period. For pre-crash period the adjustment term α_1 is significant at 10% level, while α_2 is not significant at any meaningful level. For post-crash period, we obtain similar results. This provides evidence that price adjustments only take place in the stock market. In other words, if the stock prices and the futures prices deviate, the stock prices will move closer to futures prices while futures prices can be seen as exogenous. Coefficients for lagged returns also corroborate the above conclusion. We test the hypothesis whether past futures return Granger-causes present stock returns. In other words, we test whether $b_{i,12} = 0$ for all lags i with a Wald test. For both the pre-crash period and the post-crash period, the p-values are practically zero. We also test whether past stock prices Granger-causes present futures prices. For the pre-crash period, we see a P-value of 0.035, and it suggests that stock return also Granger-causes futures returns. However, during the post-crash period there is no evidence for the above relationship at any meaningful significance level as the P-value is 0.82. Comparing across markets, we can conclude that the Granger-causality from the futures market to the stock market is much stronger than the other way around. Comparing across time, we see that either the market crash itself or Chinese government regulations diminished the impact of the stock market on the futures market; however, the futures market still has a statistically significant impact on the stock market.

[Figure 1]

[Figure 2]

Figure 1 and Figure 2 report the P-values from the rolling window analysis. We pick window size m=500. We observe that p-values for the Granger non-causality test from lagged futures returns to stock returns are practically zero for all subsamples except for the periods during which Chinese government adopted new regulatory policies on futures trading, hence there is strong evidence of causality at any standard level of significance. It is especially worth noting that data around observation 4000 corresponds to the days around July 6, and observation 6000 corresponds to late August. The P-values spikes at exactly the same time period when new barriers to entry are introduced. In other words, futures prices have no prediction power in the few days following the introduction of each new barriers. On the other hand, P-values for the test from lagged stock returns to futures returns vary across time but is hardly lower than the 0.05 threshold. This conforms to what is suggested by our theoretical model: changes in futures returns causes change in stock returns while stock returns should have little predictive power on futures returns.

6.2 Volatility Spillover Results

[Table 8]

Table 8 presents the result of volatility spillover Q-tests. It shows that volatility transmission from the futures market to the stock market is significant if we only consider the first lag. Volatility transmission from the stock market to the futures market is significant for the first two lags. P values are slightly smaller for spillover from stock market to the futures market than the other way around. The results show weak evidence for volatility spillover from the futures market to the stock market before the market crash and a slightly stronger spillover from the stock market to the futures market. After the stock market crash, there is only evidence for spillover from the futures market to the stock market, but no evidence for the other direction.

[Figure 3]

[Figure 4]

Figure 3 and Figure 4 present the results from the rolling window analysis with a window size of 2500. We report the P-values for the first three lags as our simulation study indicates that they have the proper size and power. We can observe from Figure 3 that there is significant volatility spillover form the futures market to the stock market at the first lag during the larger part of the pre-crash period. P-value goes up after the market crash. Comparing Figure 4 with Figure 3, we find that P-values are generally higher in Figure 3 except for a brief period. This indicates that volatility spillover from the futures market to the stock market is stronger than that in the other direction in most sub-periods.

We note that the full-sample results from our volatility spillover tests differ from price causality results. Whereas futures prices show a much stronger effect on the stock prices, futures volatilities have a weaker effect on stock volatilities. Moreover, mean causality from the stock market to the futures market is never significant for any extended period of time as shown in the rolling window analysis. On the contrary, there is significant volatility spillover from the stock market to the futures market during a period of 1000 samples, or approximately 20 trading days. This might imply that volatility transmission follow a different mechanism than price transmission. This hypothesis, however, needs further support from theoretical studies.

6.3 Volatility Spillover Bootstrap

Though our simulation results show that our volatility spillover tests work well if the data generation process is bivariate GARCH; however, it is highly unlikely that our empirical data comes from such a simplistic process. More specifically, our Q test requires the GARCH residuals to be not only uncorrelated but also independent, and we cannot guarantee independence without prior knowledge about the true data generating process. Therefore we adopt a more robust test for volatility spillover using the dependent wild bootstrap method introduced in Shao (2010), where independence is not assumed.

Our bootstrap method follows the procedure below:

1. We divide our centered squared standardized residuals obtained from step (2) of our previous volatility spillover test, $\{\hat{u}_{S,t}\}$ and $\{\hat{u}_{F,t}\}$, into blocks of size $b = \lfloor\sqrt{n}\rfloor$ where n is the sample size. There will then be $k = \left\lfloor\frac{n}{b}\right\rfloor$ blocks in total for each set of residuals. Note that it is very likely that $n \bmod (b) \neq 0$, so we need to append the remaining data into the last block and its size turns into $b^* = b + n \bmod (b)$.
2. We generate i.i.d. Normal (0, 1) random numbers $\{z_i |\ i = 1,2, \ldots, k\}$. Then we define $w_t = z_i\ for\ t \in \{\ t \mid \hat{u}_{i,t} \in\ i^{th}\ block\}$ such that $w_1 = z_1, w_2 = z_1, \ldots, w_{b+1} = z_2, \ldots, w_{2b+1} = z_3$, and etc.
3. We calculate our bootstrapped correlation coefficient $\hat{\rho}^{dwb}(h)$ for lag h according to the formula below where $x_t = \hat{u}_{S,t}$ and $y_t = \hat{u}_{F,t}$:

$$\hat{\rho}^{dwb}(h) = \frac{1}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t y_t - \overline{x_t}\ \overline{y_t})^2}} \cdot \frac{1}{n}\sum_{t=1+h}^{n} w_t \left(x_t y_{t-h} - \frac{1}{n}\sum_{t=1+h}^{n} x_t y_{t-h}\right) \qquad (19)$$

4. We repeat the above steps M times to obtain M sample correlations $\hat{\rho}^{dwb}(h)$ for each lag h, and calculate the Ljung-Box Q statistics $Q_i^{dwb}(h)\ for\ i = 1, \ldots, M$ using the same formula as in step (3) of our original test method. Finally we calculate the P-value $\hat{P}_M^{dwb}(h)$ where h denotes the maximum lag. $I(\cdot)$ is an indicator function, and $Q(h)$ is exactly the same value in step (3).

$$\hat{P}_M^{dwb}(h) = \frac{1}{M}\sum_{i=1}^{M} I\left(Q_i^{dwb}(h) \geq Q(h)\right) \qquad (20)$$

6.3.1 Bootstrap Simulation

We investigate the size and power of our bootstrap method through simulation. There are 10,000 samples, and M=1000 bootstrap samples. We report the rejection rate for those 10,000 repetitions. The data generating process is the same as the one in our previous volatility spillover simulation. The results are reported in tables below.

Table 9: Volatility Spillover Bootstrap Rejection Frequencies: No Spillover

Sample Size	1000			2500			5000		
Lags	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1
1	0.0149	0.0614	0.1166	0.0105	0.0497	0.1074	0.0106	0.0529	0.1002
2	0.0098	0.0515	0.1112	0.0079	0.0469	0.1017	0.0094	0.0503	0.0993
3	0.0079	0.0506	0.1047	0.0083	0.0479	0.0998	0.0096	0.0495	0.0991
4	0.0075	0.0458	0.1044	0.0075	0.047	0.0999	0.0093	0.0485	0.0964
5	0.0061	0.0451	0.1003	0.0075	0.0467	0.1053	0.0081	0.0468	0.097
10	0.0061	0.0446	0.0949	0.0077	0.0451	0.0962	0.0069	0.0459	0.0952
15	0.0051	0.0388	0.0927	0.0069	0.0435	0.0928	0.0074	0.0471	0.0883
20	0.0044	0.0372	0.0854	0.0076	0.0431	0.0902	0.0072	0.0473	0.0894

Table 10: Volatility Spillover Bootstrap Rejection Frequencies: Weak Spillover

Sample Size	1000			2500			5000		
Lags	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1
1	0.0118	0.0883	0.1823	0.0471	0.2197	0.3599	0.169	0.4494	0.6032
2	0.0382	0.2016	0.3443	0.2378	0.5631	0.7318	0.6929	0.9141	0.9568
3	0.0774	0.3195	0.5027	0.5018	0.8207	0.9127	0.9453	0.9921	0.9974
4	0.1171	0.4235	0.6131	0.6951	0.9236	0.9723	0.9864	0.9984	0.9998
5	0.1578	0.492	0.6807	0.8067	0.963	0.9862	0.994	0.9985	1
10	0.2135	0.572	0.7562	0.918	0.9858	0.9965	0.9966	0.999	0.9999
15	0.1867	0.5307	0.7226	0.9054	0.9834	0.9958	0.9968	0.999	0.9999
20	0.1592	0.48	0.6783	0.8834	0.9774	0.9918	0.9967	0.999	0.9999

Table 11: Volatility Spillover Bootstrap Rejection Frequencies: Strong Spillover

	1000			2500			5000		
Lags	0.01	0.05	0.1	0.01	0.05	0.1	0.01	0.05	0.1
1	0.027	0.1618	0.3061	0.1526	0.4472	0.6168	0.4846	0.7974	0.8934
2	0.0824	0.3474	0.5254	0.505	0.8231	0.9157	0.9295	0.9906	0.9973
3	0.1646	0.4998	0.6883	0.767	0.9516	0.984	0.9882	0.9985	0.9997
4	0.2344	0.6088	0.7832	0.8875	0.9841	0.9956	0.9942	0.999	0.9998
5	0.2879	0.6699	0.8309	0.9285	0.9914	0.9978	0.9961	0.9993	0.9999
10	0.3581	0.7366	0.8778	0.9681	0.9959	0.9982	0.9976	0.9995	1
15	0.3178	0.6974	0.8466	0.9642	0.9952	0.9982	0.9975	0.9995	1
20	0.2752	0.6476	0.8123	0.9588	0.9945	0.9978	0.9974	0.9996	1

The “No-Spillover” case show that our test statistics has a size close to its theoretical rejection rate for the first two lags but significantly smaller size at higher lags. The rejection rates, however, monotonically improve with an increased sample size. In the “Weak-Spillover” and “Strong-Spillover” cases, we find low power when the sample size is 1000, and relatively reasonable power after the second lag when the sample size is 2500 and 5000. This suggests that our test statistics have proper size and power when the sample size is larger than 2500 and when we look at the second or the third lags.

6.3.2 Bootstrap Results

[Table 12]

By looking at the second and the third lags suggested by our simulation, we find that our bootstrap results corroborate with the results found in Table 4. There is some evidence for bidirectional volatility spillovers before the stock market crash, and the spillover from the stock market to the futures market is stronger than the other direction. After the crash, there is still evidence for volatility spillover from the futures market to the stock market but no evidence for the other direction. This reinforces our belief that volatility spillover follows a different mechanism than causality in prices.

7. Conclusion

Using high frequency data, we examine the causal relationship in prices and in volatility between China's CSI 300 stock index and its futures contract. Our data cover both a period of low barriers to entry and a period of rising barriers. In this way, we not only examines if the temporal relationship between the two assets has become more aligned with those observed in developed markets six years after the initial study by Yang, Yang, and Zhou (2010), but also provides empirical evidence for the financial theory that high barriers of entry hurts price discovery performance of the futures market. Specifically, we test for Granger causality between the prices in the two markets using a vector error correction model (VECM) and test for volatility spillovers with a Q-test based on Ljung and Box (1978) and a test proposed by Hong (2001). We further validate our spillover test results by performing a more robust dependent wild bootstrap method introduced in Shao (2010).

We find that changes in CSI 300 futures prices consistently Granger-cause changes in CSI stock prices during the pre-crash period. Significant bidirectional volatility spillover exists during the pre-crash period. This might indicate that after five years of development the causal relationship between the futures market and the stock market has become aligned with those observed in developed markets. After the stock market crash, the futures price has a less consistent effect on the stock price. Futures prices can help predict stock prices in some sub-periods but not in others. In the first few days following the introduction of each new barriers, futures prices invariably have no prediction power. There is still significant volatility spillover from the futures market to the stock market after the crash, but there is no evidence for the other direction. The above results might provide evidence that barriers to entry indeed affects the price discovery performance of the futures market, confirming what is suggested by financial theories. Furthermore, the results might indicate that changes in prices and changes in volatility are transmitted through different channels between the stock market and the futures market. The plausibility of latter hypothesis is worth further theoretical studies.

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Table 5. VECM Lag (The reported lag is the underlying lag in its VAR form and will be 1 lag more than the actual VECM lag)

Lag	Log Likelihood	FPE	AIC	HQIC	SBIC
0	13742.7	7.70E-07	-8.40155	-8.40021	-8.39782
1	29820.7	4.10E-11	-18.2297	-18.2257	-18.2186
2	30228.5	3.20E-11	-18.4766	-18.47	-18.458
3	30304.3	3.10E-11	-18.5205	-18.5112	-18.4944*
4	30316.7	3.10E-11	-18.5257	-18.5137*	-18.4921
5	30322.4	3.10E-11	-18.5267	-18.512	-18.4857
6	30331.2	3.10E-11	-18.5296	-18.5123	-18.4812
7	30335.4	3.10E-11	-18.5298	-18.5097	-18.4739
8	30338.1	3.10E-11	-18.5289	-18.5063	-18.4656
9	30342.5	3.10E-11	-18.5292	-18.5039	-18.4584
10	30355.7	3.1e-11*	-18.5348*	-18.5068	-18.4566
11	30357.7	3.10E-11	-18.5336	-18.5029	-18.4479
12	30359.7	3.10E-11	-18.5324	-18.499	-18.4392

Note: This table reports the log likelihood and relevant information criterion for VECM with different underlying VAR lags. We pick the number of lags by minimizing AIC, so lag 10 is selected. * indicate the minimum for each information criterion.

Table 6. VECM Estimated Parameters-Pre-Crash

	Coefficient	Value	P-value
$EC \rightarrow \Delta P_{S,t}$	α_1	-0.01188	0.0825
$\Delta P_{S,t-i} \rightarrow \Delta P_{S,t}$			
	$b_{1,11}$	-0.48418	
	$b_{2,11}$	-0.2236	
	$b_{3,11}$	-0.09625	
	$b_{4,11}$	-0.0736	
	$b_{5,11}$	-0.00891	
	$b_{6,11}$	-0.01854	
	$b_{7,11}$	-0.06959	
	$b_{8,11}$	-0.08093	
	$b_{9,11}$	-0.11133	
$\Delta P_{F,t-i} \rightarrow \Delta P_{S,t}$	All Lags		0
	$b_{1,12}$	0.496977	
	$b_{2,12}$	0.207368	
	$b_{3,12}$	0.102724	
	$b_{4,12}$	0.069703	
	$b_{5,12}$	0.063191	
	$b_{6,12}$	0.038888	
	$b_{7,12}$	0.072941	
	$b_{8,12}$	0.079499	
	$b_{9,12}$	0.084777	

$EC \rightarrow \Delta P_{F,t}$	α_2	0.00423	0.6163
$\Delta P_{S,t-i} \rightarrow \Delta P_{F,t}$	All Lags		0.0352
	$b_{1,21}$	0.008261	
	$b_{2,21}$	0.056169	
	$b_{3,21}$	0.035088	
	$b_{4,21}$	0.042147	
	$b_{5,21}$	0.054152	
	$b_{6,21}$	0.040237	
	$b_{7,21}$	-0.021	
	$b_{8,21}$	-0.0165	
	$b_{9,21}$	-0.08384	
$\Delta P_{F,t-i} \rightarrow \Delta P_{F,t}$			
	$b_{1,22}$	-0.05525	
	$b_{2,22}$	-0.06942	
	$b_{3,22}$	-0.03435	
	$b_{4,22}$	-0.01666	
	$b_{5,22}$	-0.02722	
	$b_{6,22}$	-0.03709	
	$b_{7,22}$	0.007815	
	$b_{8,22}$	0.005418	
	$b_{9,22}$	0.04194	

Note: This table reports the estimated value of VECM parameters with 9 lags (or 10 underlying VAR lags). Chi-square statistics and its associated p-value are the results of Wald tests. Since we test for the null-hypothesis that the diagonal terms for all lags are zero, we only provide test statistics in the all lags section. Each lag is not individually tested. The first column indicates the direction of Granger (non)-causality implied by the parameters.

Table 7. VECM Estimated Parameters-Post-Crash

	Coefficient	Value	P-value
$EC \rightarrow \Delta P_{S,t}$	α_1	-0.01456	0.0238
$\Delta P_{S,t-i} \rightarrow \Delta P_{S,t}$			
	$b_{1,11}$	-0.27234	
	$b_{2,11}$	-0.08783	
	$b_{3,11}$	0.00442	
	$b_{4,11}$	-0.0186	
	$b_{5,11}$	0.00214	
	$b_{6,11}$	0.000802	
	$b_{7,11}$	0.026884	
	$b_{8,11}$	-0.01323	
	$b_{9,11}$	0.004476	
$\Delta P_{F,t-i} \rightarrow \Delta P_{S,t}$	All Lags		0
	$b_{1,12}$	0.280807	
	$b_{2,12}$	0.058472	

	$b_{3,12}$	0.038507	
	$b_{4,12}$	0.015444	
	$b_{5,12}$	0.031271	
	$b_{6,12}$	0.01095	
	$b_{7,12}$	-0.00288	
	$b_{8,12}$	0.01458	
	$b_{9,12}$	-0.01601	
$EC \rightarrow \Delta P_{F,t}$	α_2	0.00871	0.3105
$\Delta P_{S,t-i} \rightarrow \Delta P_{F,t}$	All Lags		0.8239
	$b_{1,21}$	0.053762	
	$b_{2,21}$	0.001524	
	$b_{3,21}$	0.02115	
	$b_{4,21}$	0.028774	
	$b_{5,21}$	0.073777	
	$b_{6,21}$	0.03906	
	$b_{7,21}$	0.029947	
	$b_{8,21}$	0.018665	
	$b_{9,21}$	0.013234	
$\Delta P_{F,t-i} \rightarrow \Delta P_{F,t}$			
	$b_{1,22}$	-0.00967	
	$b_{2,22}$	-0.04847	
	$b_{3,22}$	-0.00179	
	$b_{4,22}$	-0.04063	
	$b_{5,22}$	-0.02511	
	$b_{6,22}$	-0.03868	
	$b_{7,22}$	-0.0234	
	$b_{8,22}$	-0.00132	
	$b_{9,22}$	-0.05367	

Note: This table reports the estimated value of VECM parameters with 9 lags (or 10 underlying VAR lags). Chi-square statistics and its associated p-value are the results of Wald tests. Since we test for the null-hypothesis that the diagonal terms for all lags are zero, we only provide test statistics in the all lags section. Each lag is not individually tested. The first column indicates the direction of Granger (non)-causality implied by the parameters.

Table 8. Volatility Spillover Test Results

Time Period	Pre-Crash		Post-Crash	
Lags (j)	Futures to Stock P-value	Stock to Futures P-value	Futures to Stock P-value	Stock to Futures P-value
1	0.0180	0.0177	0.0105	0.6308
2	0.0563	0.0474	0.0362	0.8753
3	0.0838	0.0898	0.0832	0.9662
4	0.0766	0.1444	0.1254	0.8436
5	0.1149	0.2201	0.2040	0.9226

6	0.1804	0.2759	0.2914	0.9364
7	0.2582	0.2813	0.3740	0.9678
8	0.3413	0.2657	0.4422	0.9811
9	0.4357	0.2682	0.5299	0.9913
10	0.5237	0.2713	0.6219	0.9894
11	0.4775	0.2445	0.7046	0.9946
12	0.5598	0.2447	0.7771	0.9968
13	0.5502	0.2707	0.8249	0.9973
14	0.5034	0.2961	0.8720	0.9987
15	0.5786	0.2354	0.9103	0.9990
16	0.6433	0.2729	0.9063	0.9984
17	0.4835	0.2895	0.9078	0.9984
18	0.5501	0.3296	0.9280	0.9992
19	0.4825	0.1838	0.9439	0.9995
20	0.5262	0.0647	0.9514	0.9997

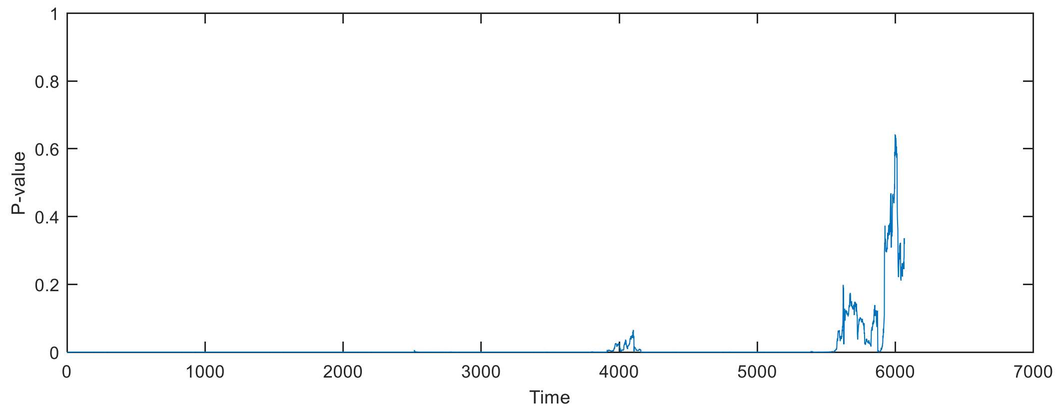
Note: This table reports the P-values for the volatility spillover tests on both the pre-crash period and the post-crash period. H0 is that there is no volatility spillover. Rejection of H0 at lag j indicates the existence of volatility spillover up till the jth lag.

Table 12. Bootstrap Volatility Spillover Test Results

Time Period	Pre-Crash		Post-Crash	
Lags (j)	Futures to Stock P-value	Stock to Futures P-value	Futures to Stock P-value	Stock to Futures P-value
1	0.0254	0.0187	0.0076	0.6481
2	0.0649	0.0472	0.0319	0.8897
3	0.0774	0.0678	0.0905	0.9712
4	0.0612	0.0996	0.13	0.8756
5	0.134	0.1872	0.25	0.94
10	0.5567	0.3025	0.6827	0.993
15	0.585	0.2281	0.928	0.9991
20	0.5647	0.0608	0.9645	0.9999

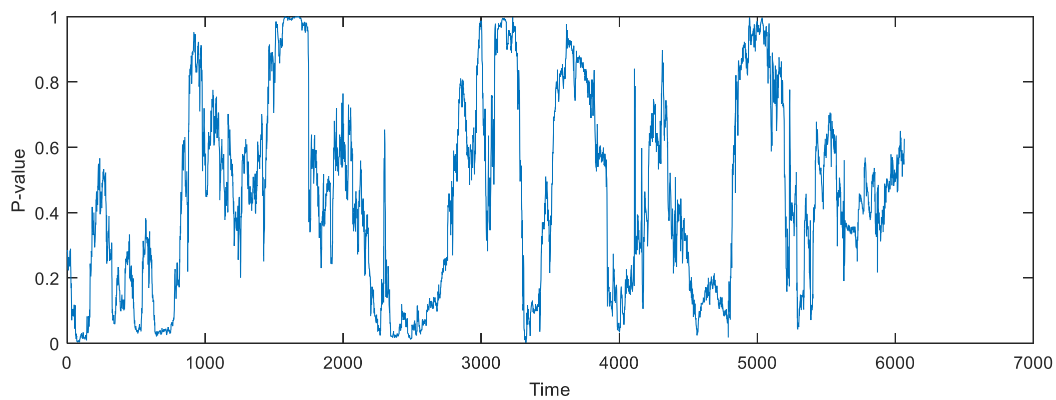
Note: This table reports the P-values for the bootstrap volatility spillover tests on both the pre-crash period and the post-crash period. H0 is that there is no volatility spillover. Rejection of H0 at lag j indicates the existence of volatility spillover up till the jth lag.

Figure 1. Rolling Window P-value for Granger non-causality from Index Futures Returns to Index Returns



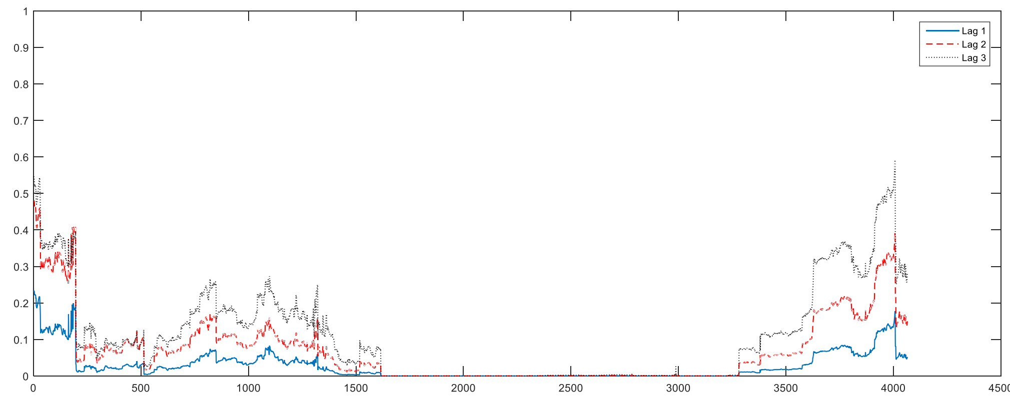
Note: We perform rolling window analysis to test Granger non-causality with a window size of 500. Each point on the line is the p-value of the Wald test for the sub-period of 500 5-minute periods. Time is measured in 5-min intervals. So 1000 is the 1000th 5-minute interval in the data. It is worth noting that data around 4000 corresponds to the days around July 6, and 6000 corresponds to late August. The P-values spikes at exactly the same time period when new barriers to entry are introduced.

Figure 2. Rolling Window P-value for Granger non-causality from Index Returns to Index Futures Returns



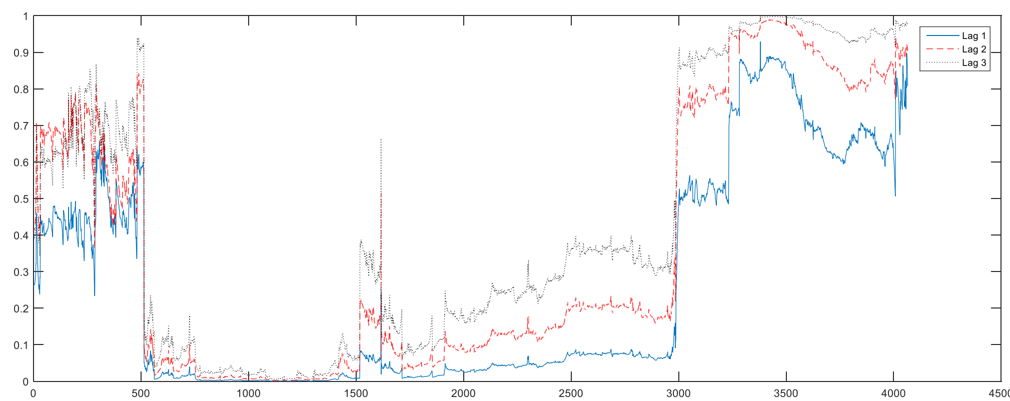
Note: We perform rolling window analysis to test Granger non-causality with a window size of 500. Each point on the line is the p-value of the Wald test for the sub-period of 500 5-minute periods.

Figure 3. Rolling Window P-value for Volatility Spillover from Index Futures Returns to Index Returns



Note: We perform rolling window analysis to test volatility spillover from the futures market to the stock market with a window size of 2500. Each point on the line is the p-value of the Q test for the sub-period of 2500 5-minute periods. The largs being reported are the first three lags.

Figure 4. Rolling Window P-value for Volatility Spillover from Index Futures Returns to Index Returns



Note: We perform rolling window analysis to test volatility spillover from the stock market to the futures market with a window size of 2500. Each point on the line is the p-value of the Q test for the sub-period of 2500 5-minute periods. The lags being reported are the first three lags.

Appendix

Timetable of CFFE Policies after June 2015 Market Crash (only those directly affecting the CSI 300 are included)

Announcement Date	Effective Date	Policy
7/3	7/6	Limit single account intraday buy/sell volume to 1200 contracts
7/31	8/3	Start charging a fee of 1 Yuan for placing a buy/sell order or cancelling an existing order
8/25	8/26	Increase transaction fee to 1.5/10,000 of total transaction amount
8/25	8/26-28	Increase margin requirement from 10% to 12%, 15%, and 20% in the next three days
8/28	8/31	Increase margin requirement to 30%
9/2	9/7	Increase transaction fee to 23/10,000 of total transaction amount
9/2	9/7	Increase margin requirement to 40%